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Modelling and Evaluation of Work Zone Queues: Istanbul Case Study

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ABSTRACT

Road/lane closures due to maintenance works adversely affect the traffic conditions, causing delays in the various locations of the whole network. In Istanbul, Metropolitan Municipality charge the companies for the planned closure of the highways for a given time interval using simple spreadsheet calculations. These calculations include assumed capacity and speed values for each type of highway. In this paper, it is aimed to establish a methodology for the work zone evaluation that considers seasonality in demand and spatiotemporal variability in the flow and capacity. This goal will be achieved by observing and assessing the characteristics of İstanbul roadways and work zone areas. After the assessment, a traffic microsimulation software, namely PARAMICS, was used to simulate various road and work zone combinations to produce traffic data, including queue length, waiting times, vehicle speeds, flow and density of work zone section. Various machine-learning models were developed and their performance on test data will be analyzed. The selected model was used as a sub-model to estimate the expected delays, speeds and accelerations on different road types, different demands and lane closure combinations. A second sub-model used the delay, speed and acceleration values to estimate the total excess user cost due to road closure with determined delay-cost parameters.

1. Introduction

Traffic conditions and road network of a city are affected negatively when there is a road or lane closure due to infrastructure or maintenance works, incidents and similar events. Road and lane closures also cause accidents in the roadways, these accidents can be prevented using traffic signs according to standards of General Directorate of the Highways [1]. These kinds of nonrecurring events cause undesired traffic conditions such as increased delays and traffic congestion. As the duration of these conditions increase, the negative impact starts to sprawl into other roads connected to this road as well. To avoid further issues such as secondary accidents and minimize the duration of these road blocking events, metropolitan municipalities quote a price for these events for being able to compensate for the losses of other system users.

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The impact of these events is investigated in many different studies. Decrease in the capacity of a road due to lane closures for various combinations (i.e., closing 2 out of 3 lanes, 1 out of 2 lanes, 3 out of 5 lanes and so on.) is observed in different sites of Texas by Dudek *et al*., [2] and their findings were used in the Highway Capacity Manual [3]. Texas Transportation Institute developed a DOS-based program called Queue and User Cost Evaluation of Work Zones (QUEWZ) that uses the equations from Highway Capacity Manual 1993 [4]. Seshadri *et al*., [5] did some modifications on this QUEWZ model, which was called QUEWZ-E and used it to estimate the fuel costs and emissions. Their work concentrates on the indirect environmental cost induced by the work zones. However, later research in the urbanized Texas areas made by Krammes *et al.,* [6] showed that work zone flow capacities are actually higher than the values given in the Highway Capacity Manual 1994. Thus, a higher base capacity value is suggested to be added into the manual. The resulting capacity is computed with the use of adjustment factors. Adjustments are applied for the intensity of the work activity, proportion of heavy vehicles in the traffic stream and presence of entrance ramps near the beginning of the lane closure.

Estimating the work zone capacities and potential queue lengths became the focus of many different studies. A regression model for work zone capacity estimation with explaining variables such as number of closed lanes, percentage of heavy vehicles, grade and work intensity was developed in the study of Kim *et al.,* [7]. Regression results found to be better at predicting the actual work zone capacity than the applications of Highway Capacity Manual. Karim *et al*. [8] trained a radial basis function neural network to estimate the work zone capacity and queue length. The goal was to develop a general model with simple major parameters, such as number of initial (before the incident) and final (during the incident) lanes, geometry, and percentage of trucks in the flow. Even though neural network models provide good results with high amounts of data, they give no insight about the underlying dynamics due to being a black box model. Different approaches for the calculation of the work zone flow capacity and queue length were tested in the studies of Schnell *et al.* [9] and Chitturi *et al.* [10]. These approaches include Highway Capacity Software, Synchro, CORSIM, NetSim, FRESIM, QuickZone, QUEWZ 92 and Ohio Department of Transportation Spreadsheet. Results show that although none of the approaches give the accurate results, the QUEWZ 92 and spreadsheets give better results than the traffic microsimulations under saturated flow conditions. In the study of Heiden *et al*., [11] a deterministic and stochastic capacity analysis for both long and short term work zones was conducted. Deterministic analysis is done using the van Aerde model [12], taking the apex value in the speed-flow curve whereas stochastic analysis is conducted using the lifetime analysis for capacity as in the paper of Geistefeldt *et al.,* [13]. In this study, the capacity assumed to follow a Weibull distribution. Capacity is hard to measure since excessing the capacity means a breakdown, analogous to death in lifetime analysis. On the other hand, capacity is a stochastic value meaning that exceeding the realization of a random variable causes the breakdown. This type of data, not specific to a value but a range, is called censored data. Li *et al*., [14] tried to determine the work zone lane capacities along multilane corridors by conducting a data analysis. After inspecting 5 days of 5-minute interval data from 7 different work zones, it was observed that shifted log-normal distribution fitted well to the capacity of work zones. Determining the capacities by themselves may not be always sufficient for practical cases. It is also important to determine and predict the cost of these unwanted road closures.

The cost of a closure for a traveler can be more than just one thing; that is, travel time delay. In addition to travel time delays, reduction in average speed, increased emissions and other factors can all be considered as costs and it is important to be able to predict the effects on the travelers and on the overall system. Jiang [15] constructed a model for estimating the excess user cost at highway work zones. The model uses given average values of hourly arrival rate, hourly queue discharge rate, free flow speed and speed under congestion to calculate a stochastic expected cost. Model calculates the costs of deceleration delay, reduced speed delay, acceleration delay, vehicle queue delay, excess speed change cycle and excess running costs. By utilizing a single layer artificial neural network which was trained by considering speed of road segments, work zone length, work zone duration, work zone starting time and open to closed lane ratio, Du *et al*., [16] trained a model to find the estimated speed during a lane closure. By predicting the work zone speed, it was then possible to predict and calculate the delays as well. The artificial neural network model then was further improved by Du *et al*., [17] in another study with a hybrid model. The updated model estimates the work zone capacity using a support vector machine. After that, this capacity is used with upstream traffic volume and normal speed in order to compute the weighted speed of the no lane closure case. The single hidden layer neural network uses this speed for each section and section's distance to the work zone as inputs and predicts the speed values during the lane closure. Another data mining tool was also utilized in the study of Edara *et al*., [18]. In that study a random forest model was presented in order to predict travel delays by utilizing historical work zone data. The random forest model uses 27 variables including work zone start time, date, location, length, configuration (number of lanes, number of closed lanes, and place of the closed lanes) and past travel times for work zone segment which was recorded for 3 weeks on upstream and downstream of work zone. By determining the capacity for the work zones and the potential costs for the travelers, it can be considered that there is enough information for presenting solutions for avoiding these unwanted issues related with a lane closure.

With different methods presented in the studies, it is possible to minimize the costs for all travelers and improve the efficiency of the overall road network. Chien *et al*., [19] developed a numerical optimization method for lane closures of two-way two-lane highways with diverted traffic. The method assumes deterministic queues and then determines the optimal schedules and lengths of the work zones considering the hourly traffic, maintenance times, setup and idle time costs. Their method minimizes the weighted sum of user and agency costs. This method was then further improved by the study of Jiang *et al*., [20] in which a method for all road and lane closure combinations that also considers the seasonality in the traffic flows and nighttime working costs was proposed. The improved method uses a neural network with simulated annealing in order to have quick and non-local optimal results. By considering the traffic diversion and effect of managed lanes on long-term and short-term work zones Chien *et al*., [21] developed a work zone schedule optimization algorithm. Genetic algorithm was utilized as the solution algorithm to this multidimensional combinatorial optimization problem. These presented solutions should also be inspected in real life situations in order to evaluate their performance. Pesti *et al*., [22] proposed a model that gathers data from Bluetooth reader pairs and finds a queue length estimate, average travel time and average speed. However, the method does not do predictions for the future, only assesses the measures in the given data.

Literature shows that complex solutions in the past might give comparable, if not worse, results to simple approaches such as spreadsheets and regression, and they take a lot of time and data to implement. However, it should be noted that gathering data became much easier and data mining and machine learning tools are improved considerably. Machine learning tools are used predominantly in the recent years for work zone impact analysis. The characteristics of work zone flow changes from place to place thus directly using any former developed method may not yield good results for Istanbul. In addition, most methods in the literature do not consider oversaturated conditions and long-term queues and uses deterministic queues instead of stochastic queues for simplification. Therefore, a new method was developed in this study which aims to overcome these shortcomings. The goals of this study is to develop a method to predict the experienced cost of temporary lane closures in Istanbul traffic due to roadworks or other reasons using the road and traffic related features. By determining the delay, it will be possible to create fair billing method that considers the closure duration and incentivize the maintenance companies to affect the traffic as little as possible.

2. Theory

The developed model was used with several algorithms, namely Ordinary Least Squares Regression, Bayesian Linear Regression, Support Vector Machine, Random Forest, Gradient Boosting, K-nearest Neighbor Regression and Gaussian Process, in order to compare the performances in the prediction of cost estimation of lane or road closures.

2.1 Ordinary Least Squares Regression

Ordinary Least Squares Regression is a linear regression method where the parameters of the model are chosen to minimize the sum of squared prediction error. This method assumes that explanatory variables are independent of each other and dependent variable has a linear relationship with the explanatory variables. Even though it is a fast method and has high interpretability, it performs poorly when there are nonlinear relationships.

2.2 *Bayesian Linear Regression*

Bayesian Linear Regression is a variant of linear regression where the parameters of the model are assumed to be random variables with a prior (commonly uninformative) distribution.

The main objective of this method is to determine the posterior distribution for the model parameters instead of finding a single best value of the model parameters. The posterior distribution of model parameters is found using the Bayesian update rule, which is conditional upon the training inputs and outputs:

$$P(\beta|y,X) = \frac{P(y,|\beta,X) \times P(\beta|X)}{P(y|X)} \tag{1}$$

where P(β|y,X) is the posterior probability distribution, P(y,|β,X) is the likelihood of the data, P(β|X) is the prior probability of the parameters and P(y|X)is a normalization constant. The parameters are found by maximizing the likelihood of posterior distribution. If a flat prior is applied, the results become identical to the Ordinary Least Squares. Bayesian Linear regression gives the uncertainty of the model and the model parameters. Bayesian regression has confidence intervals on its fitted values as well as its predictions. It also has a self-regularization structure, the model penalizes the unnecessary variables. In fact if zero-mean normal (gaussian) priors are given for model parameters the regularization is equivalent to the ridge regression. Posterior distributions for certain priors have exact solutions however for others heuristic sampling methods such as Markov Chain Monte Carlo (MCMC) must be used to estimate the parameters which makes Bayesian Linear Regression computationally expensive.

2.3 Support Vector Machine

Support Vector Machine regression is a regression technique that is derived from the Support Vector Machine algorithm which is designed for classification task. Support Vector Machine is defined as “maximum margin classifier” which means the classification boundary is the line which maximizes the distance (margin) from the different classes. The regression part works in a similar way where regressor tries to fit all the data points inside a predefined small margin. For non-linear cases slack variables (ξ_i) which are added for allowing misclassification of noisy data points are introduced. The problem becomes an optimization problem in which the aim is to maximize the margin between different classes. The formulation is as follows:

$$minimize\ \frac{1}{2}||w||^2 + C\ \sum_{i=1}^{n} \xi_i \tag{2}$$

Such that

$$y_i(w^T x_i + b) \geq 1 - \xi_i \tag{3}$$

$$\xi_i \geq 0$$

The parameter C can be adjusted to manage over-fitting. 2/(||w||) is the margin width. In addition, Support Vector Machine (and Regression) becomes even more powerful by using the kernel trick. The kernel trick is a way to quickly map the data points into another higher dimension. Nonlinear boundaries can turn into linear boundaries by mapping the data points into a plane with higher dimension than the original. This feature makes the Support Vector Machine able to work with nonlinear data.

2.4 Random Forest

Random Forest Regression is a parallel ensemble learning technique where weak regressors (such as Classification and Regression Trees) are used alongside to make robust and powerful predictions. The weak regressors are trained with different bootstrapped subsets of the data. The subsets that are fed to the regressors have different features and different data points. This bootstrapping method makes the weak regressors different from each other and prevents overfitting. Weak classifiers vote their predictions and the highest voted value is given as the final prediction of the random forest. Random Forest is robust to overfitting and hyper-parameter selection.

2.5 Gradient Boosting

Gradient Boosting Regression is a sequential ensemble learning technique where the error of a regressor is predicted by the next regressor in the line. It is similar to the random forest algorithm however due to its sequential nature it is prone to overfitting. If its hyper-parameters are set optimally gradient boosting may outperform the random forest however it is not guaranteed.

2.6 K-Nearest Neighbor Regression

K-Nearest Neighbor Regression is the regression counterpart of k-Nearest Neighbor clustering algorithm. New data point is estimated as the average of the k nearest (according to the Euclidean distance metric) neighbors. K-Nearest Neighbor is a fast algorithm. By changing the total number of clusters, k, the error rate on a validation set can be observed. It is generally expected that when k=1 the model will overfit the training data. However, up to a certain value, the error rate will decrease and then it will restart to increase again. The minimum point in that trial and error process, which is also called the minima of elbow curve, will provide the optimum number of clusters to be used for the data set. However, it requires multiple runs and the fact that the method lacks any underlying model, makes the method rely on memorization. It can also become very memory intensive.

2.7 Gaussian Process

Gaussian Process is the nonparametric counterpart of the Bayesian linear regression. Bayesian linear regression puts priors on the parameters of the model whereas Gaussian Process puts a Gaussian (normal) prior on the regression function itself and obtains posterior distribution for the regression function. Method assumes that the outputs of the regression function is jointly Gaussian with a mean and variance function. The variance function can be chosen arbitrarily and works similar to the kernel function of the support vector machine. This makes Gaussian process able to work with nonlinear data and also give uncertainty information about its predictions.

3. Methodology

The flow chart of the developed method is presented in the figure below (Figure 1). For the delay cost calculation, a machine learning model predicts the experienced delay time throughout the closure period. This delay is discretized into smaller time steps of 1 minute and it is multiplied with the demand at the given time and resulting product is aggregated over time. If the demand is constant and delay is predicted as a mean value, no discretization is required. For the increased fuel cost calculation, speed and acceleration values after a road closure are predicted and discretized into small time steps of 1 minute. After the discretization and application of fuel consumption equation of Equation (5), the resultant value is multiplied by the demand and aggregated. This value gives the estimated fuel consumption for the vehicles under road closure. The same calculation is applied for the predicted speed, acceleration and fuel consumption of the same road type without a lane closure and is calculated. The difference between these two fuel consumption values is the increased fuel consumption.

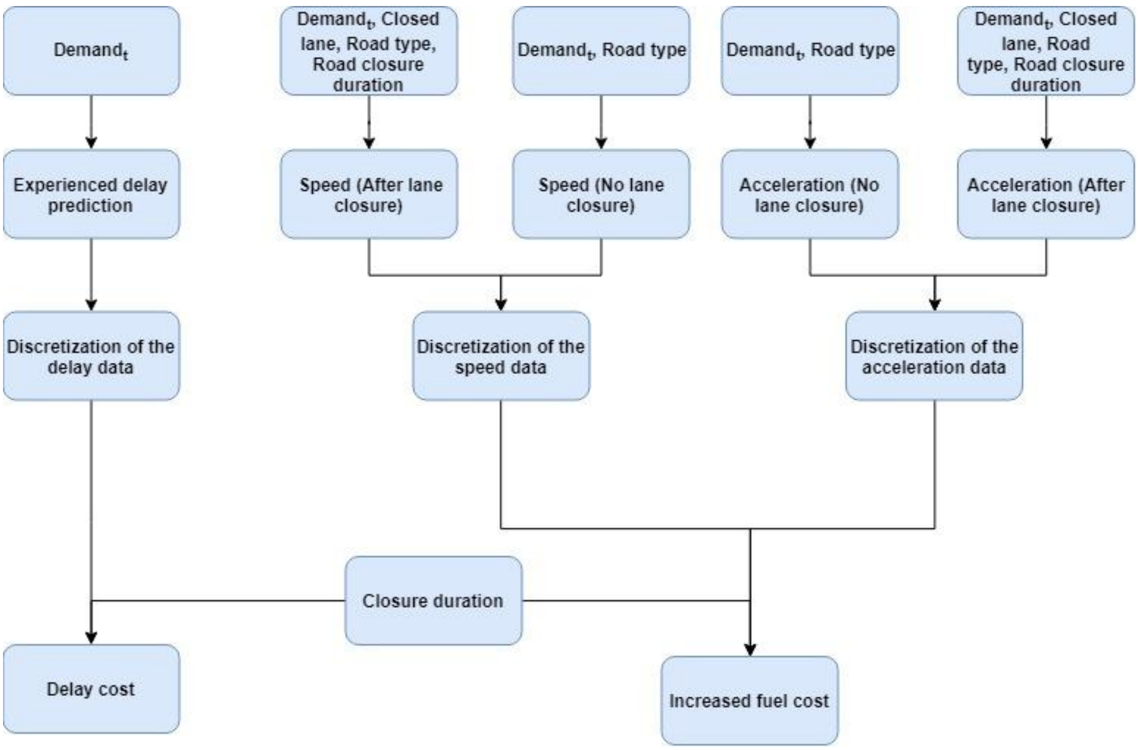

Fig 1. The flow chart of the developed method

This paper focuses on the lane closures of three major highway types of Istanbul: Freeway, Primary Arterial and Secondary Arterial (Table 1). The characteristics of these highways are investigated in study [23] and found characteristics such as number of lanes, lane widths, speed limits and hourly demand levels are used in the modeling of related highways. After fixing the legislative and geometric features of the road, demand values are determined incrementally based on the density observed for the given demand. Traffic dynamics differ on a road depending on the demand at that time. The demand can be broadly classified into 3 categories: low demand, medium demand and high-near capacity demand. In case of low demand, there are minimal interactions between vehicles whereas for medium demand scenarios there are considerable interactions and platooning vehicles can be observed from time to time. High demand cases are where almost all the vehicles are in interaction with the nearby vehicles. The interaction for a pilot vehicle can be defined as any effect from other vehicles that inhibits the free movement of the pilot vehicle. Interaction may be platooning, not being able to change lanes, keeping safe distance and so on. In Greenshield's flow-density curve (Figure 2), low demand corresponds to the initial part of the curve where flow increases almost linearly with increase in density, high demand corresponds to the part close to the inversion (peak) point and medium demand is the section between the two [24].

Table 1
Road classes and their properties

Road Class	Number of Lanes	Speed Limit (km/hr)	Lane Width (m)
Freeway	4	120	13.2
Primary arterial	3	90	9.9
Secondary arterial	2	50	6.0

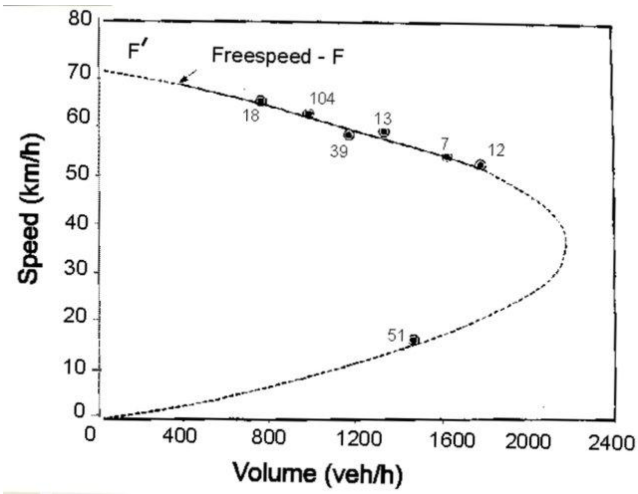

Fig 2. Greenshields' original (1935) speed-flow diagram as reproduced by F Hall

During the surveying period on the IBB Traffic Map [25], it was found that majority of the lane closures last between 20 minutes and 60 minutes. According to these results, it was decided that in the simulations the lane closure scenarios will last 20, 30, 45 and 60 minutes. The simulation was conducted using PARAMICS software and repeated 30 times for each road type, demand, closure lane (including no closure for comparison) and closure duration combination. The closure happens in the middle of 1 km basic roadway section (no entries or exits). The upstream is 9 km to cope with any prolonged queue, downstream is 2 km for clear disposal. The system is designed that way to prevent over complication that comes from the merge-in and exit points. Similar to the fluid dynamics, intersections create chaotic behavior in upstream and downstream locations and since all intersections are different and yield different results, the system is simplified to a basic roadway (Figure 3). Statistics related to the traffic flow and features such as speed, density, flow occupancy and headway are collected on the road section in the simulation environment. However, in real life situations this is not always possible for all road sections. It is important that the developed model is robust and can be applied for real-life scenarios. Therefore, only the easily observable and predictable features of road and traffic are used during the modeling, which are demand level, lane closure duration, closed lane and road type.

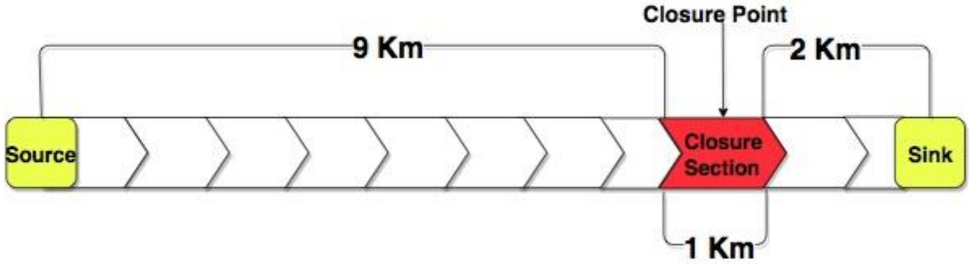

Fig 3. The sketch of the simulation model

3.1 Data

For analysis, the dataset utilizes the following parameters presented in the table below (Table 2).

Table 2
Dataset parameters for the analysis

Road Property	Label
Time index	Simulation time of the recorded data
Closure duration (minutes)	Cases with 20, 30, 45 and 60 minutes of lane closure were used
Demand (veh/hr)	Demand on freeway: 3500 veh/hr, 4500 veh/hr, and 7500veh/hr. Demand on primary arterials: 2500 veh/hr, 3500 veh/hr and 5500 veh/hr. Demand on secondary arterials: 1500 veh/hr, 2500 veh/hr and 3500 veh/hr
Closure lane 1 (if closure is on the 1st lane in the simulation)	If true: 1 Otherwise: 0
Closure lane 2 (if closure is on the 2nd lane in the simulation	If true: 1 Otherwise: 0
Closure lane 3 (if closure is on the 3rd lane in the simulation)	If true: 1 Otherwise: 0
Closure lane 4 (if closure is on the 4th lane in the simulation)	If true: 1 Otherwise: 0
Freeway (if the given road type is a freeway)	If true: 1 Otherwise: 0
Primary Arterial (if the given road type is a primary arterial)	If true: 1 Otherwise: 0
Secondary Arterial (if the given road type is a secondary arterial)	If true: 1 Otherwise: 0
Delay (Second)	The time difference between crossing the road section with and without a lane closure
Mean speed of vehicles (m/s)	-
Mean acceleration of vehicles (m/s^2)	-

For improved modeling results and ease of analysis, some adjustments to the dataset were made. These adjustments are as follows:

1. Accident lane and road types are converted from categorical to one-hot-encoded variables. Although some machine learning algorithms can work with the categorical variables some of them such as SVM and Neural Networks, perform poorly. Thus, categorical variables were converted to one-hot-encoded variables.
2. It is always standard practice to scale or standardize the features and dependent variable in order to overcome the domination of larger valued features over smaller valued features and prevent numerical inaccuracies and biased results. Therefore, all the features are scaled to [0, 1] range. Although standardization is more robust than scaling, in terms of outliers, standardization of binary variables is not a good practice.
3. Features of the dataset should be independent from each other. By looking at the visualization of the correlation matrix of the features of the dataset (Figure 4), it can be observed that there are no important correlations between explanatory variables.

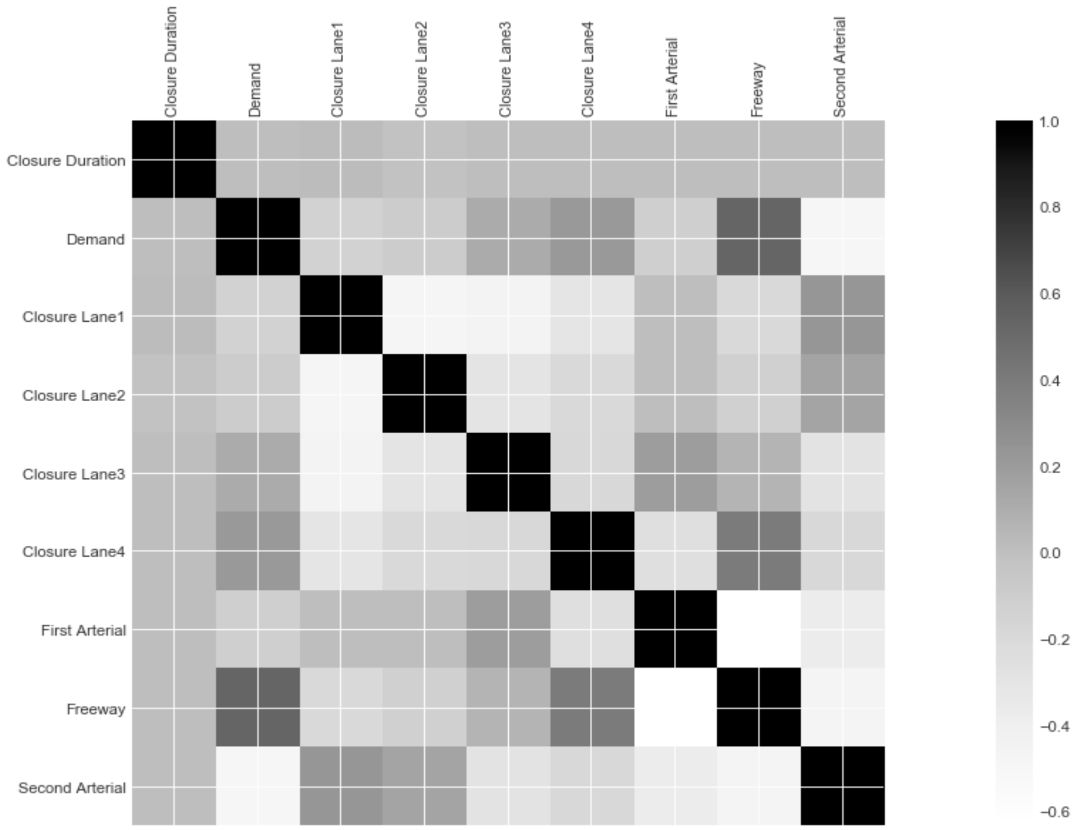

Fig 4. Visualization of the correlation matrix of the features of the dataset.

3.2. Cost Calculation

Lane closures have two cost components which are time delay cost and increased fuel consumption cost. The first one depends mostly on the speed of the road section while the latter depends on both acceleration and speed. For both calculation methods time is discretized into small time units of Δt. Δt is chosen to be 1 minute to capture the average changes in the traffic in a precise manner.

3.2.1 Delay cost calculation

Delay cost is the total delay experienced by all the users of the road section multiplied by their respective value of time. The inflation adjusted [26] value of time for vehicle types in Istanbul can be found in the following table (Table 3).

Table 3
Value of time for vehicle types in Istanbul (Adjusted for inflation from 2011 February 2019 [26,27])

Vehicle Type	Value of Time (TL/min)	Modal Share (%)
Passenger Car	0.56	62.00
Shuttle	3.56	20.00
Van	1.24	15.00
Truck	2.02	3.00
Weighted Average Vehicle	0.59	-

The total delay was calculated by applying the equation (1):

$$\sum_{t=1}^{T} \sum_{i=1}^{I} Demand_t\ Delay_t\ \zeta_i\ p_i\ \Delta t,\ I \in Passenger\ Car, Shuttle, Van, Truck \quad (4)$$

Where, 〖Demand〗 _t is the demand at time section t, 〖Delay〗 _t is the delay at time section t, ζ_i is the unit value of time for the vehicle type i, p_i is the proportion of demand that belongs to the vehicle type i and Δt is the unit time step.

3.2.2 Increased fuel consumption calculation

Increased fuel consumption was calculated by subtracting the fuel consumption when there is no lane closure from fuel consumption when the designated lane is closed. The fuel prices in the city of Istanbul [28] are provided in the following table (Table 4).

Table 4
Fuel prices in the city of Istanbul (as of February 2019 [28])

Fuel Type	Fuel Price (TL/L)	Fuel Price (TL/g)
Gasoline	6.04	0.00427632
Diesel	6.01	0.00500032
Gasoline	6.04	0.00427632

The fuel consumption cost can be calculated using following equations:

$$\sum_{t=1}^{T} \sum_{i=1}^{I} Demand_t\ FuelConsumption_{ti}\ \beta_i\ p_i\ \Delta t,\ I \in Passenger\ Car, Shuttle, Van, Truck \quad (5)$$

Where 〖Demand〗 _t is the demand at time section t, 〖FuelConsumption〗 _t is the fuel consumption of vehicle type i at time section t β_i is the unit value of fuel type for the vehicle type i p_i is the proportion of demand that belongs the vehicle type i and Δt is the unit time step.

According to the Euro IV Standard [29] the following equations are utilized for calculating the fuel consumption:

$$P_e = 0.001 \left[mgv_t(0.009 + 4.13x10^{-5}v_t) + \frac{\rho_{air}}{2} C_d A v_t^3 + 1.05 m a_t v_t \right] \quad (6)$$

$$F_c = \frac{P_e b_e}{3.6 v_t} \quad (7)$$

Where P_e is engine power in kW, C_dA is a constant equal to 0.585, ρ_{air} is the density of air (1.225 kg/m^3), v_t is speed in m/s, a is acceleration in m/s^2, m is mass in kg, g is gravitational acceleration in m/s^2, $F_c$is fuel consumption in g/km and $b_e$is Brake-Specific Fuel Consumption (BSFC) in g/kWh (205 for gasoline 250 for diesel).

3.2.3 Experienced delay prediction model

Experienced delay during a lane closure is calculated as the mean time difference between crossing the road section with a lane closure and without a lane closure. The delay is a time dependent property which increases after the closure occurs. The increased delay value will last for some time and afterwards it will decrease back to its regular values (Figure 5).

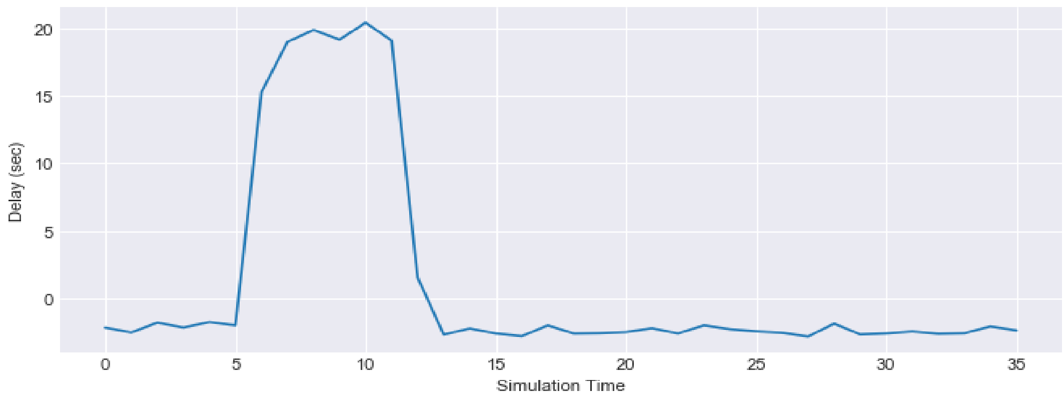

Fig 5. The mean experienced delay in a case of lane closure.

By ignoring the warm up and cool down periods and fluctuations the mean experienced delay time could be predicted as a regression problem using various machine learning algorithms. Ordinary Least Squares Regression, Bayesian Linear Regression, Support Vector Regression, Random Forest Regression, Gradient Boosting Regression, k-Nearest Neighbor Regression and Gaussian Process were compared for their prediction error.

3.2.4 Speed and acceleration prediction model

Speed and acceleration during a lane closure are calculated as the mean vehicle speeds and accelerations on the road section. Speed and acceleration, similar to the experienced delay, are time dependent properties. The progression of speed (Figure 6) and acceleration (Figure 7) during the simulation can be seen in the figures below.

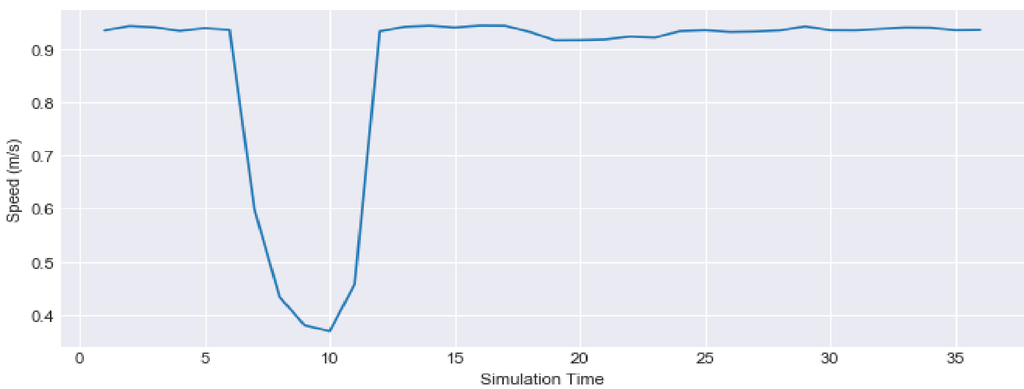

Fig 6. The mean speed in a case of lane closure

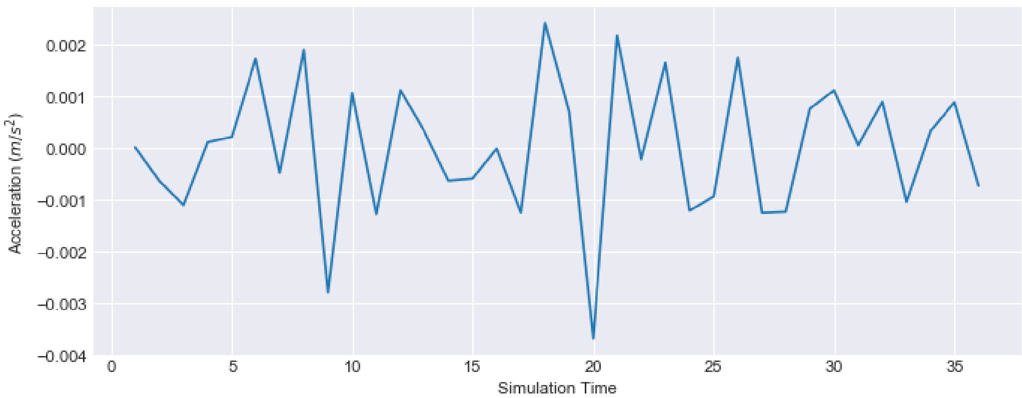

Fig 7. The mean acceleration in a case of lane closure

Similar to delay prediction, speed and acceleration prediction were done using Ordinary Least Squares Regression, Bayesian Linear Regression, Support Vector Regression, Random Forest Regression, Gradient Boosting Regression, k-Nearest Neighbor Regression and Gaussian Process. The models were compared according to their prediction error values.

4. Analysis

For performance metric of each method, 10-Fold Cross Validation with mean squared error was repeated 5 times. In each cross-validation step grid search was applied for hyper parameters of SVR, Random Forest, Gradient Boosting, k-Nearest Neighbor and Gaussian Process. The hyper-parameters and their ranges are given in the table below (Table 5).

Table 5
Hyper-parameters of the tested methods

Tested Method	Hyper-parameters	
SVM	Kernel	RBF, Linear, Polynomial
	c	1, 10, 100, 1000
	Degree	2, 3, 4, 5
	Gamma	1e-3, 1e-4
Random Forest	Maximum Features	sqrt(n), log(n), n/2
	Minimum Samples Split	2, 5
	Number of Estimators	100, 200, 300, 400, 500
Gradient Boosting	Number of Estimators	100, 200, 400, 500
	Learning Rate	0.01, 0.05, 0.08, 0.10, 0.12
	Maximum Depth	2, 3, 4, 5
	Maximum Features	sqrt(n), n
k-Nearest Neighbor	Number of neighbors	3, 5, 7, 10, 12, 15
Gaussian Process	Kernel	RBF, Dot product, Rational quadratic

After the cross validation it was observed that for all regression purposes gradient boosting and random forest yield the best testing error results. Gradient Boosting Regression is generally better at regression purposes than Random Forest Regression. However, it must be kept in mind that Gradient Boosting is prone to overfitting to the testing data if its hyperparameters are not set ideally whereas Random Forest is highly robust to its hyperparameters and has low risk of overfitting due to its parallel structure. It is also seen that linear methods of Linear Regression and Bayesian regression and kernel methods of Support Vector Machine and Gaussian Process have given inferior results. This shows that used kernels were not able to catch the required dimension or were overfitting to the testing data. Traditional kernel functions are tried in this study and there are many custom kernels specific to different tasks. It should be noted that kernel selection is a tedious task and is even harder than hyperparameter tuning.

The testing mean squared error values (for scaled values) for delay and speed prediction for each algorithm's best parameters are presented in the table below (Table 6).

Table 6
Mean squared error (MSE) for predictions

ML Algorithm	MSE for Delay Prediction	MSE for Speed Prediction
Linear Regression	0.04520	0.02540
Bayesian Regression	0.04510	0.02530
SVM	0.04470	0.02478
Random Forest	0.02260	0.01370
Gradient Boosting	0.02390	0.01350
k-Nearest Neighbor	0.02710	0.01760
Gaussian Process	0.04510	0.02540

For random forest method, the best hyper-parameters were as follows:

i. Maximum features: 4
ii. Minimum samples split: 5
iii. Number of estimators: 400

When gradient boosting method was considered, the best results were obtained for the following hyper-parameters:

i. Learning rate: 0.1
ii. Maximum depth: 4
iii. Maximum number of features: $\sqrt{n}$ where n is the number of features in the given dataset
iv. Number of estimators: 500

For each prediction task, the mean absolute deviation for chosen algorithm is given in Table 5.

Table 7
Testing mean absolute deviation

	Delay Prediction	Speed Prediction	Acceleration Prediction
Mean Absolute Deviation (%)	24.31	32.75	30.18

For selected closure scenarios, the predicted total user cost is calculated and provided in Table 6. There were 4 phenomena present in the given results. The first one was that with increasing closure durations, ceteris paribus, the total cost increases. These increases in the cost were not linear and this was because prolonged closures create different dynamics than the short ones. The second phenomenon was that with increasing demand the closure cost also increases. This relationship was again nonlinear. The third observation was that changing the closure lane changes the cost in a distinct manner. The closure cost of closing the lane 1 (the right-most lane) was cheaper than closing the lane 4 (the left-most lane). This might be because the rightmost lane is usually underutilized and the flow from this lane compared to the other lanes affects the traffic flow in a minimalistic way. On the other hand, closing the lane 2 was costlier than closing any other lane. This was again an expected event, since closing a lane in the middle of the road is an unexpected event and also the blocked vehicles in this lane are flowing into the adjacent two lanes, one of which is the left-most lane (the lane with the highest speed values). The explained phenomena can also be observed in more detail in the following figures (Figure 8-10).

Table 8
Road closure cost values for selected parameters

Closure Duration (minutes)	Demand (veh/hr)	Closed Lane	Road Type	Total Cost (TL)
20	1900	1	Primary Arterial	6723.52
30	1900	1	Primary Arterial	11146.45
40	1900	1	Primary Arterial	18548.47
50	1900	1	Primary Arterial	23185.59
60	1900	1	Primary Arterial	24903.76
30	2500	1	Freeway	25170.82
30	2500	2	Freeway	39042.83
30	2500	3	Freeway	26516.00
30	2500	4	Freeway	31538.82
60	2500	4	Freeway	65641.53
30	1500	1	Secondary Arterial	8505.82
30	1800	1	Secondary Arterial	10206.98
30	2000	1	Secondary Arterial	11341.09

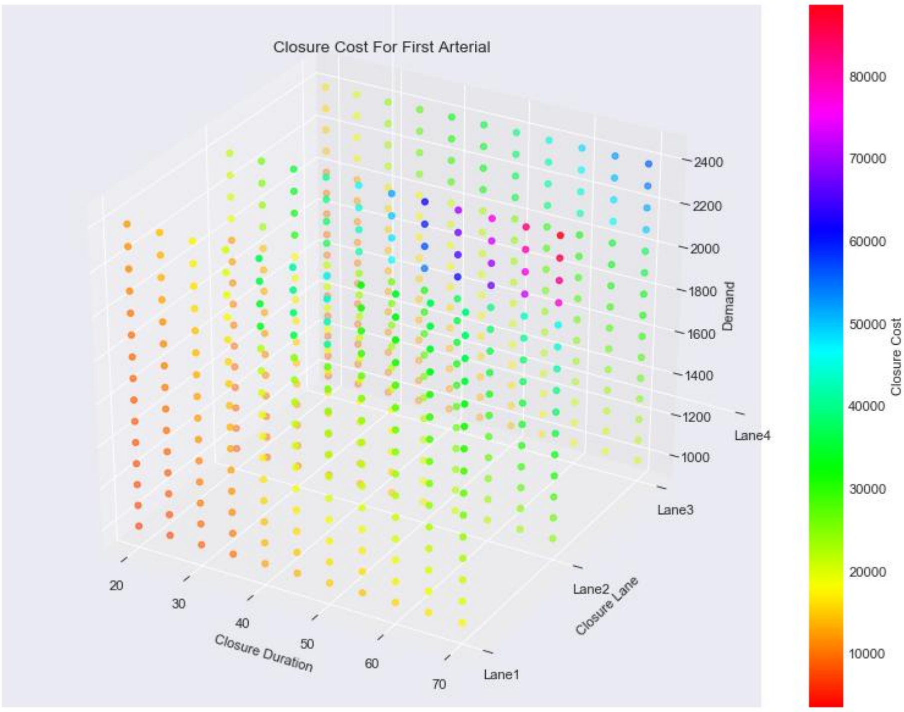

Fig 8. Road closure cost for primary arterials

In Figure 8, the cost of lane closure increases monotonically with closure duration and demand. On the other hand, it can be seen from the colors that closure lane is not an ordinal property meaning the order of lane is not the same with the order of closure cost in any sorting. The middle lane has a higher expected closure cost than other lanes.

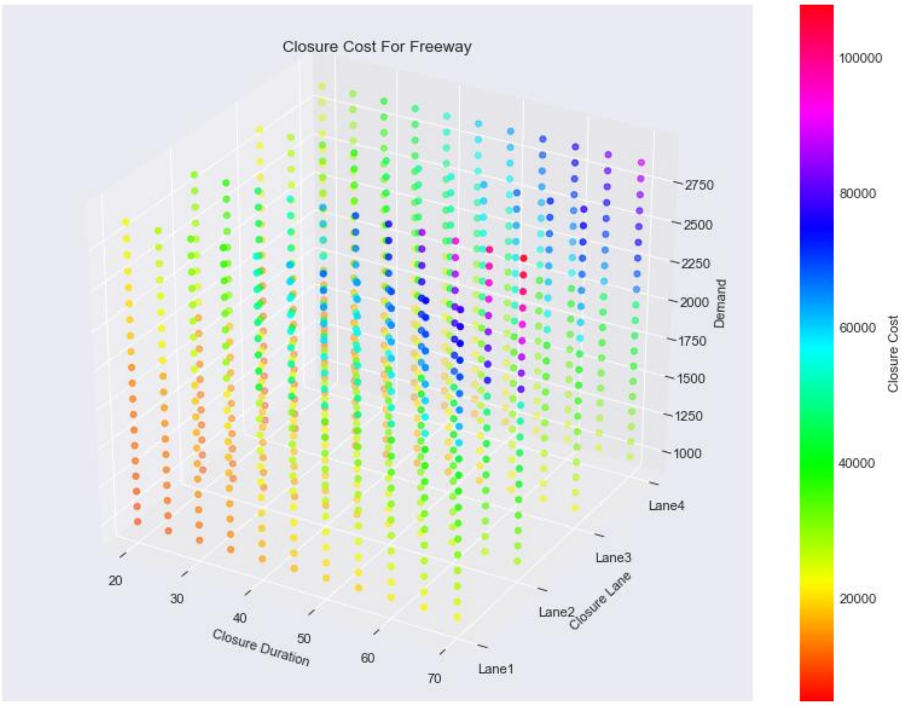

Fig 9. Road closure cost for freeways

Looking at Figure 9, it can be observed that the figure is similar to the Figure 8. If inspected carefully it can be detected that the rate of change in the color spectrum is also not uniform. This non-uniformity was caused by the direct effect of nonlinearity in the delay and fuel costs.

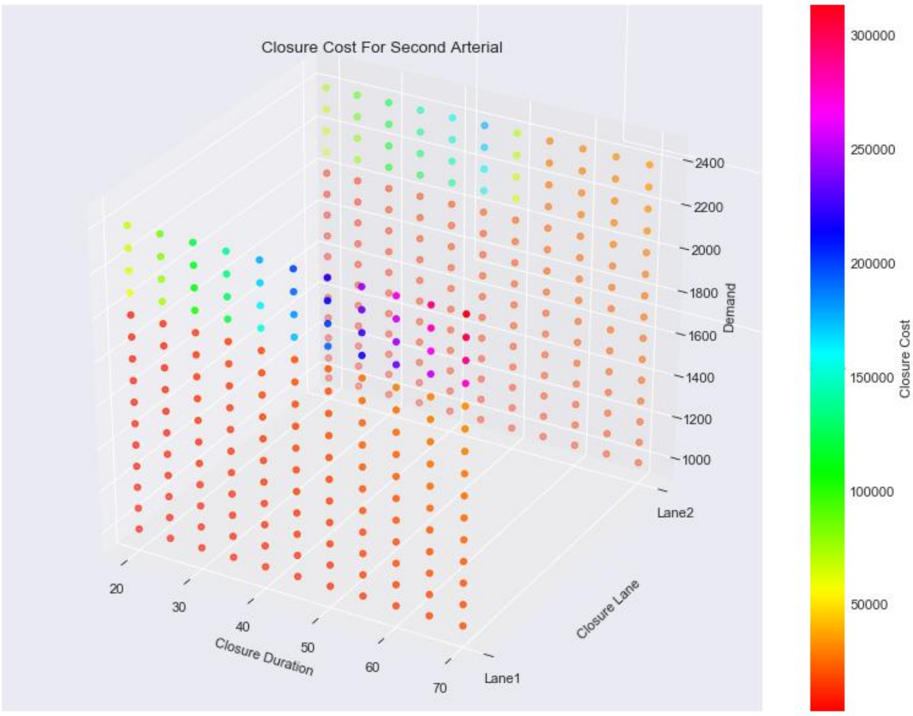

Fig 10. Road closure cost for secondary arterials

In Figure 10, since both lanes are the only alternative of the other and there is no lane in the middle their contribution to the cost is similar. However, for higher demand values it is observable that lane 1 is more important in terms of affecting the traffic after being closed.

5. Conclusion and Future Work

In this study, the cost prediction methods for lane closures were reviewed and a method to predict the expected cost of temporary lane closures in Istanbul traffic is developed using the road and traffic related features. It was observed that gradient boosting and random forest give comparable results. Even though the prediction accuracy is not very high, it should be noted that only "knowable" features are taken as input for the algorithm and not real time data. This design was selected since the authorities do not have access to the real time traffic data before the lane closure and also ITS systems are not present on every road section and detailed flow statistics cannot be gathered. Theoretically the prediction accuracy could have been easily improved by utilizing more features. However, by doing so the presented method would become impractical.

The predicted costs values taken from the model are reviewed and it is seen that results are realistic and sound. The changes in parameters result in changes in the cost values in the expected directions. This indicates that our trained model was successful at learning and successful at replicating the real life outcomes.

If instantaneous values are used instead of using mean values, the problem of speed/acceleration and delay prediction could also be thought as time series forecasting using exogenous variables. Auto Regressive Integrated Moving Averages (ARIMA) and Seasonal Auto Regressive Moving Averages Exogenous (SARIMAX) are widely used for time series forecasting. However, since the aim of the study was predicting the time series without having any knowledge about previous data points, there can be no fitting period. This property converts our problem to a one-to-many sequence prediction problem. Long Short-Term Memory (LSTM) is a type of Recurrent Neural Networks (RNN) that can handle time dependent data with its memory and make one-to-one, one-to-many, many-to-one and many-to-many predictions. Using an LSTM network can theoretically improve our results by making our model a dynamic nonlinear model that can capture the time dependent movements in the data. However, due to its computational cost, LSTM network was not used in this study; however, their additional performance improvements should be analyzed in further studies.

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Conflicts of Interest

The authors declare no conflicts of interest.

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